Journal of Mathematical Psychology 84 (2018) 1–12

Contents lists available at ScienceDirect

Journal of Mathematical Psychology

journal homepage: www.elsevier.com/locate/jmp

Review

Parameter estimation of the Linear Phase Correction model by hierarchical linear models

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HIGHLIGHTS

- The Linear Phase Correction model captures the synchronization of movements with metronomes.
- Its current parameter estimation method is called "bounded Generalized Least Squares" method.
- It averages estimates from multiple synchronization sequences and is biased in certain conditions.
- We present (a) an extended Linear Model that integrates multiple sequences within a single model and (b) a Mixed-Effects Model, that additionally incorporates random effects.
- To reduce the estimation biases caused by (a) a shortened sequence length and (b) between-sequence variability.

ARTICLE INFO

Article history:
Received 27 October 2017
Received in revised form 21 March 2018

Keywords:
Linear Phase Correction model
Sensorimotor Synchronization
Parameter estimation
Mixed-Effects Models
Hierarchical linear models

ABSTRACT

The control of human motor timing is captured by models that make assumptions about the underlying information processing mechanisms. A paradigm for its inquiry is the Sensorimotor Synchronization task, in which an individual is required to synchronize the movements of an effector, like the finger, with repetitive appearing onsets of an external event. The Linear Phase Correction model is a cognitive model that captures the asynchrony dynamics between the finger taps and the event onsets. However, when the synchronization periods are short and/or when there is variability between multiple sequences, the existing parameter estimation methods are biased. Therefore, this work is an approach of unbiased parameter estimation of the LPC model. Based on simulated data, we, first, present a method that integrates multiple sequences within a single model and estimates the model parameters of short sequences with a clear reduction of bias. Second, by relating random effects to the asynchronies sharing the same sequence, we show that parameters can also be retrieved robustly when there is between-sequence variability of their expected values. Since such variability is common in experimental and natural settings, we herewith propose a method that increases the applicability of the LPC model. This method can fit data from short and varied sequences, which may reduce parameter biases due, for example, to fatigue or attentional variation. This allows experimental control that previous methods are unable to provide.

Contents

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Abbreviations: CNS, Central Nervous System; SMS, Sensorimotor Synchronization; acf, auto-correlation function; acvf, auto-covariance function; LPC, Linear Phase Correction Model; OLS, Ordinary Least Squares; GLS, Generalized Least Squares; bGLS, bounded Generalized Least Squares; MLE, Maximum Likelihood Estimator; ELM, Extended Linear Model; MEM, Mixed-Effects Model

https://doi.org/10.1016/j.jmp.2018.03.008
0022-2496/

1. Introduction

Humans are able to coordinate their movements with nearby moving objects in the environment with a remarkable ease. This requires a highly timed communication of the perception–action systems underpinning the movement control. In order to investigate the underlying timing mechanisms employed by the central nervous system (CNS), researchers study participants' attempt to synchronize their movements concurrently with repetitively occurring environmental events. Synchronization can be understood as a simplified type of coordination because it is constrained in space and time. It is particularly important in activities such as music, sports, and manufacturing. Synchronizing movements was also shown to improve the interaction with the partner by increasing social attachment and cooperation (Reddish, Fischer, & Bulbulia, 2013; Valdesolo, Ouyang, & DeSteno, 2010; Wiltermuth & Heath, 2009), rapport (Miles, Nind, & Macrae, 2009), and likability (Launay, Dean, & Bailes, 2014), and it was traditionally used as a means to enhance self-esteem and obedience (Valturio, 1921).

The study of motor synchronization is mostly focused on effectors like the fingers (Repp, 2005), the forearms (Mörtl et al., 2012), or the feet (van Ulzen, Lamoth, Daffertshofer, Semin, & Beek, 2008) to be timed with external events like auditory metronomes, light displays, or interacting partner movements (Noy et al., 2017; Schmidt & Richardson, 2008).

Within the framework of event-based timing models, a successful synchronization requires the individual to (a) perceive the event onsets; (b) perceive her or his movement onset; (c) compute the asynchrony between both onsets; (d) compute the temporal progression of the repeated event series; (e) follow all these steps to predict upcoming event onsets.

Based on these perceptual processes, appropriate motor commands can be computed so that the asynchrony between the movement and the event becomes reduced to a minimum (Grush, 2004; Van Der Steen & Keller, 2013). When the external event is presented with constant temporal intervals (these may also vary slightly), this paradigm is called *Sensorimotor Synchronization* (SMS) (Repp, 2005).

There are cognitive models accounting for the empirical findings obtained from SMS tasks. Cognitive models usually use a mathematical representation, formalized as a parametrized system of equations that receives input, for example, sensory cues about the onsets and previous asynchronies and intentions to reduce the asynchrony (Jacoby, Tishby, Repp, Ahissar, & Keller, 2015; Schulze & Vorberg, 2002; Wing & Kristofferson, 1973) and produce output, for example a motor response to reduce the next asynchrony or the actual asynchrony sequence. By solving (or approximating) such systems, its parameters can be identified.

For a given input and set of parameters, these models can be challenged by comparing their analytical or simulated output with experimental observations. By systematically manipulating the input, it can be tested whether such processes – as postulated by the particular model – in fact underpin the information processing of the CNS.

Because in experiments there are always variables that can neither be manipulated nor controlled – i.e., there is noise within and outside the CNS – these problems are usually approached in a probabilistic manner. Within the framework of probability theory, a model can be defined as a parametric family of probability distributions. The combination of probability distributions (indexed by parameters) determines the distribution of the input and associates a probability of occurrence to each output. Probabilistic models are used to model cognitive abilities. Usually, the challenge is to determine how the input and the output relate to the model parameters in question (Myung, 2003).

In cognitive models of motor synchronization, the output is the sequence of asynchronies obtained from the onsets of the oscillating movements of an individual and the onsets of a repetitively appearing stimulus. Our scope is (a) to give a brief overview of such models, (b) present their current parameter estimation approaches and limitations, and (c) to introduce a novel approach of parameter estimation.

1.1. Timing models

1.1.1. Continuation tapping

In order to account for human timing processes, Wing and Kristofferson (1973) developed a probabilistic cognitive model, which describes the timing behavior of individuals who have to execute repetitive movements at constant temporal intervals. When the intervals are determined by an external metronome that suddenly stops and the individual is required to continue executing the constant movement intervals, this method is called the *Synchronization–Continuation paradigm*. Based on the variability of the movement intervals (i.e., the time between two successive taps), Wing and Kristofferson (1973) proposed the following model[1] :

$$I_j = C_j - D_{j-1} + D_j, \quad (1)$$

where I_j is the movement interval j, C_j is the internal representation of the interval I_j (time keeper), and D_j is the motor delay. The quantity I_j is the temporal response interval bounded by two

[1] For the introduction of the existing models and techniques, we used the notation of the original articles. For this reason, notations of the same variables and parameters can vary throughout this work.